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Parameters Identification of Valve Dynamic Damping System Based on LuGre Model and Adaptive Chaotic Particle Swarm Algorithm

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Abstract

In this paper, the dynamic parameters of the valve test system are identified based on a novel adaptive logistic chaotic particle swarm optimization. Three new aspects are considered in the new identification algorithm to enhance global search capability and improve identification accuracy: first, modifying particle formula, second, adding chaos to the iterative process, third, adjusting inertia weight and acceleration coefficients adaptively in the particle equations. The experimental results demonstrate that the adaptive logistic chaotic particle swarm optimization algorithm is more effective to apply for parameters identification than other algorithms.

Keywords: Adaptive Chaotic Particle Swarm Optimization, LuGre model, Parameters Identification.

1. Introduction

The accuracy of valve damping parameters is important both to make quantitative analysis for friction characteristics and to provide some reference values in valve design. Rather than mass and stiffness, which can be measured in a directly way, it is difficult to obtain damping parameters directly. It is a common way to identify damping parameters through establishing a mathematical model that can accurately describe the friction phenomenon. The appropriate friction model and identification algorithm are the sufficient conditions of identifying damping parameters.

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Many kinds of friction models have been proposed in order to identify damping parameters until now. Friction model can be classified into static model and dynamic model. It is not considered that there is no movement between two contact interfaces. Compard with static models, dynamic friction models display a more realistic state of the contact interfaces. There are many dynamic friction models, such as Dahl model, Bliman-Sorine model, Reset-integrator model, LuGre model and so on [1].

Numerous intelligent algorithms are used in parameter identification at present. Heuristic algorithm, particle swarm optimization and genetic algorithm are some cases of intelligent algorithms. A novel adaptive logistic chaotic particle swarm optimization is applied for parameters identification the valve damping test system based on LuGre friction model in this paper.

2. LuGre Friction Model

Friction is a very complex phenomenon. Many friction characteristics such as pre-sliding, friction lag and Stribeck effect bring several troubles to create system models [2]. LuGre model is continuous model which takes smooth transitions among different states. LuGre model could simulate friction phenomenon better than other friction models.

LuGre friction model describes dynamic friction characteristics in the form of first order differential equations. Mathematical description of the LuGre friction model is as follows:

$$F = \sigma_0 z + \sigma_1 \, dz/dt + \sigma_2 v \tag{1}$$

$$dz/dt = v - \sigma_0 |v| z \Big/ (F_c + (F_s - F_c) e^{-(v/v_s)^2}) \tag{2}$$

where F is friction force, v is velocity between two surfaces in contact, σ_0 is stiffness coefficient, σ_2 is viscous friction coefficient, σ_1 is micro damping coefficient, z the internal friction state, F_s the corresponds to static friction force, and F_c is Coulomb friction force. $g(v)$ captures Coulomb friction and the Stribeck effect, v_s is Stribeck velocity.

3. Particle Swarm Optimization Algorithm (PSO)

3.1 Basic PSO algorithm (BPSO)

The standard BPSO is described in vector notation as follows:

$$V(i+1) = wV(i) + c_1 r_1 (P(i) - X(i)) + c_2 r_2 (G - X(i)) \tag{3}$$

$$X(i+1) = X(i) + V(i+1) \tag{4}$$

where w inertia weight, c_1, c_2 and c_3 acceleration coefficients, r_1 and r_2 random numbers between 0 and 1.

PSO evaluates the quality of particles through fitness function rather than derivative information and certain direction of optimization. Compared with genetic algorithms, PSO has no evolution operators such as crossover and mutation. Besides, the structure is simpler and the convergence is faster.

3.2 Adaptive Logistic Chaotic Particle Swarm Optimization algorithm (ALCPSO)

Based on BPSO algorithm, three respects are improved: modifying the particle equation, adding chaos to the iterative process and adjusting inertia weight and acceleration coefficients adaptively in the particle formula. Then the three improvements are described respectively in detail. The velocity equation of the improved particle formula is as follows:

$$V(i+1) = wV(i) + c_1 r_1 (P(i) - X(i)) + r_2 (c_3 (L(i) - X(i)) + c_2 (G - X(i))) \tag{5}$$

First, modifying the particle equation: compared with equation (3), one more factor is considered in equation (5). $L(i)$ is the best position for neighborhood of $P(i)$. Adding $L(i)$ improves the ability of the global convergence. The existence of multiple neighborhoods generates the probable optimal particles. Although the convergence rate of the algorithm is influenced, global search capability is enhanced.

Second, adding chaos to the iterative process: the chaotic search of logistic mapping is applied to the algorithm, which avoids evolutionary stagnation problems probably happened in later iteration. CHAOS is as follows:

$$z_k = (k - 1/k)^2 z_g + \left[1 - (k - 1/k)^2\right] z_k \tag{6}$$

where k the current iteration, z_g the chaotic variable. z_k is chaotic vector that current particle individuals correspond to, $z_k^{'}$ is the new chaotic variable. The weights of z_g and z_k change adaptively with the further search to enhance the disturbance of the solution vector.

Third, adjusting the inertia weight and acceleration coefficients adaptively as follows: $c_1 = 1.8$, inertia weight $w = 1 - k/2T$, the acceleration coefficients c_2 and c_3 are adaptively changed with the variation of iterations, $c_2 = 1.8 \times (k/T)^2$ $c_3 = 1.8 \times (1 - (k/T)^2)$ .Adaptive changes of c_2 and c_3 ensure that $L(i)$ strong global search ability in the early time and powerful local search capability in later iterations. k is the current iteration and T is the total iteration

The damping parameter identification process of ALCPSO algorithm is as follows:

Step 1) Initialize a population of particles with random positions and velocities in the problem space, and generate chaotic variables in the method of logistic mapping, and the equation is as follows:

$$z_j^{(i+1)} = 4 z_j^{(i)} (1 - z_j^{(i)}) \tag{7}$$

where i is serial number of particle swarm individual, j is serial number of chaotic variable, z_j^i is chaotic variable that the j th parameter to be identified in the i th particle swarm individual corresponds to.

Step 2) Set up the mapping between chaotic variables and individual variables of particle swarm.

Step 3) Get individual variables of particle swarm through inverse mapping of the chaotic variables and establish the improved particle equations as follows:

$$X_j^{(i)} = X_j^{(\min)} + (X_j^{(\max)} - X_j^{(\min)}) z_j^{(i)} \tag{8}$$

Step 4) Evaluate fitness values and sort individuals according to fitness values.

Step 5) Update the best positions of individuals, best positions of neighborhoods and the global best position.

Step 6) Update the velocity and position according to equation (5) and (4).

Step 7) Return step 4) until the current iteration equals to the maximum iteration.

Step 8) Update the inferior particles that account for 30% of the current particle swarm through joining CHAOS, then return step 4).

3.3 Convergence Analysis of ALCPSO algorithm

Sphere function and Griewank function, which are well-known benchmark functions [3], are considered to verify the effectiveness of the ALCPSO algorithm. Sphere function is a kind of single extreme value function whose global minimum is 0. Griewank function is a function with multiple extreme values whose global minimum is 0.

Sphere function: $F(x)=\sum_{m=1}^{M}(x_m{}^2)$

Griewank function: $F(x)=0.00025\sum_{m=1}^{M}x_m^2-\prod_{m=1}^{M}\cos(x_m/m)+1$

ALCPSO, GA [4] and PSO [5] are applied to identify parameters of the above functions respectively, and identification results are as follows. In the paper, the dimension and the population size of these testing functions are 4 and 50 respectively. The dimension of the testing functions in the above equations is M (M=4). The search space ranges of these testing functions are both (-30, 30).

Table1. Fitness values for GA [4] PSO [5] and ALCPSO

Algorithms(T=500)	Sphere	Griewank
GA	0.0092	0.046
PSO	0.0101	0.052
ALCPSO	0.0014	0.017

Compared with these results, the fitness value of ALCPSO is smaller than PSO and GA in the application of single extreme value functions. Although the global search capabilities of three algorithms above are good in multiple extreme value functions, the accuracy of ALCPSO is higher than the other algorithms.

4. Parameters Identification of Valve Damping Test System

Valve friction pairs take the reciprocating motion in macro mode and micro-motion modes respectively in the experiments. Linear motor drives valve friction pairs to the large-travel motion in low-frequency (lower than 100Hz) mode, and piezoelectric motor drives valve friction pairs to the short-travel motion in high-frequency mode. The velocity wave of friction pairs is sinusoidal in the form of linear reciprocating motion. Change the vibration frequency when the velocity amplitude is approximately equal.

Six parameters are unknown in LuGre friction model. In PSO, population size N=50 and iteration times T=500. Identification curves are obtained as follows. The comparison curves between LuGre model friction and experimental measured friction are separately.

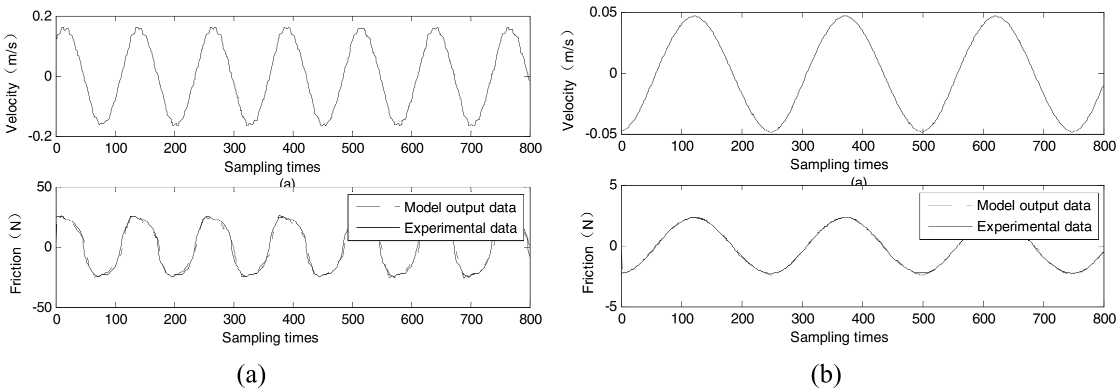

Figure1: comparison between experimental data and model output data in macro (10Hz) and micro (200Hz) modes

Table2. Parameter identification results in macro motion mode and micro motion mode

parameters	4Hz	8Hz	10Hz	20Hz	100Hz	200Hz	300Hz
F_c (N)	5.13	6.02	6.62	13.72	13.38	5.25	5.83
F_s (N)	34.27	39.17	39.84	27.22	29.29	31.27	37.21
v_s (m/s)	0.018	0.017	0.011	0.035	0.03	0.0038	0.0042
σ_2 (Ns/m)	46.34	48.66	60.34	228.1	387.5	51.31	47.91
σ_1 (Ns/m)	138.83	136.8	110.4	227.4	412.3	111.36	107.91
σ_0 (N/m)	4457.9	4286	4993	2822	2366	2016.4	1891.4

Setting velocity a constant by changing valve pairs' movement frequency, damping parameters identified are shown in table 2.

According to the above identification results, under certain velocity amplitude, identification results may change as vibration frequency changes. In addition, the damping parameters generally take not much change within certain frequency range. The damping parameters take a little change when the vibration frequency is lower than 10Hz. However, when the vibration frequency is more than 20Hz, damping parameters change a lot. Friction amplitude increasing leads to σ_2 become greater in sliding period. As frequency rises, acceleration increases, σ_1 becomes greater and σ_0 gets smaller.

5. Conclusion

In this paper ALCPSO algorithm has been presented and is applied to the identification of damping parameters of valve friction pairs. ALCPSO avoids the problem of local optimum, improve the accuracy of the parameters to be identified and is applicable to identify parameters of other nonlinear models. Experimental results show that the damping parameters can describe the dynamic process of valve damping characteristics precisely. The identification results lay the foundation for further research on valve motion characteristics. There is also some reference value in engineering applications.

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